



On the use of spectral observations in climate change studies: a review and an outlook

Xianglei Huang

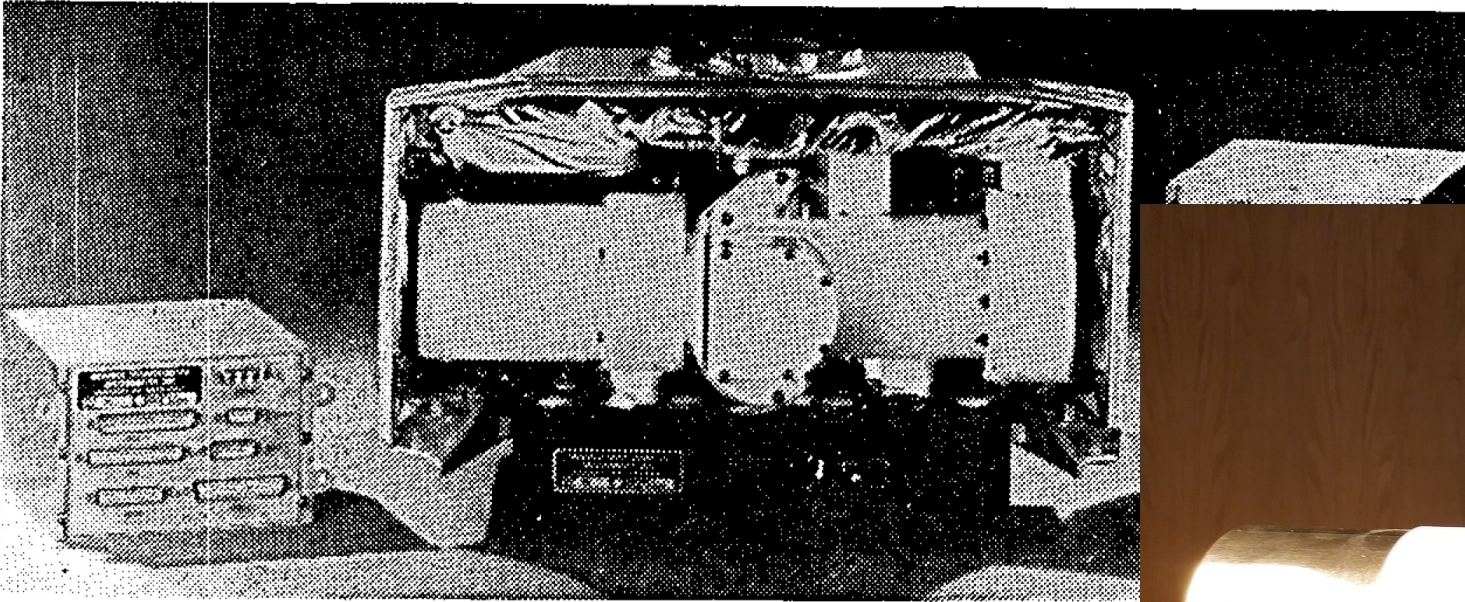
University of Michigan

Earth Radiation Budget Workshop, Hamburg, Fall 2022

Acknowledgments: CERES team, past and current students and collaborators

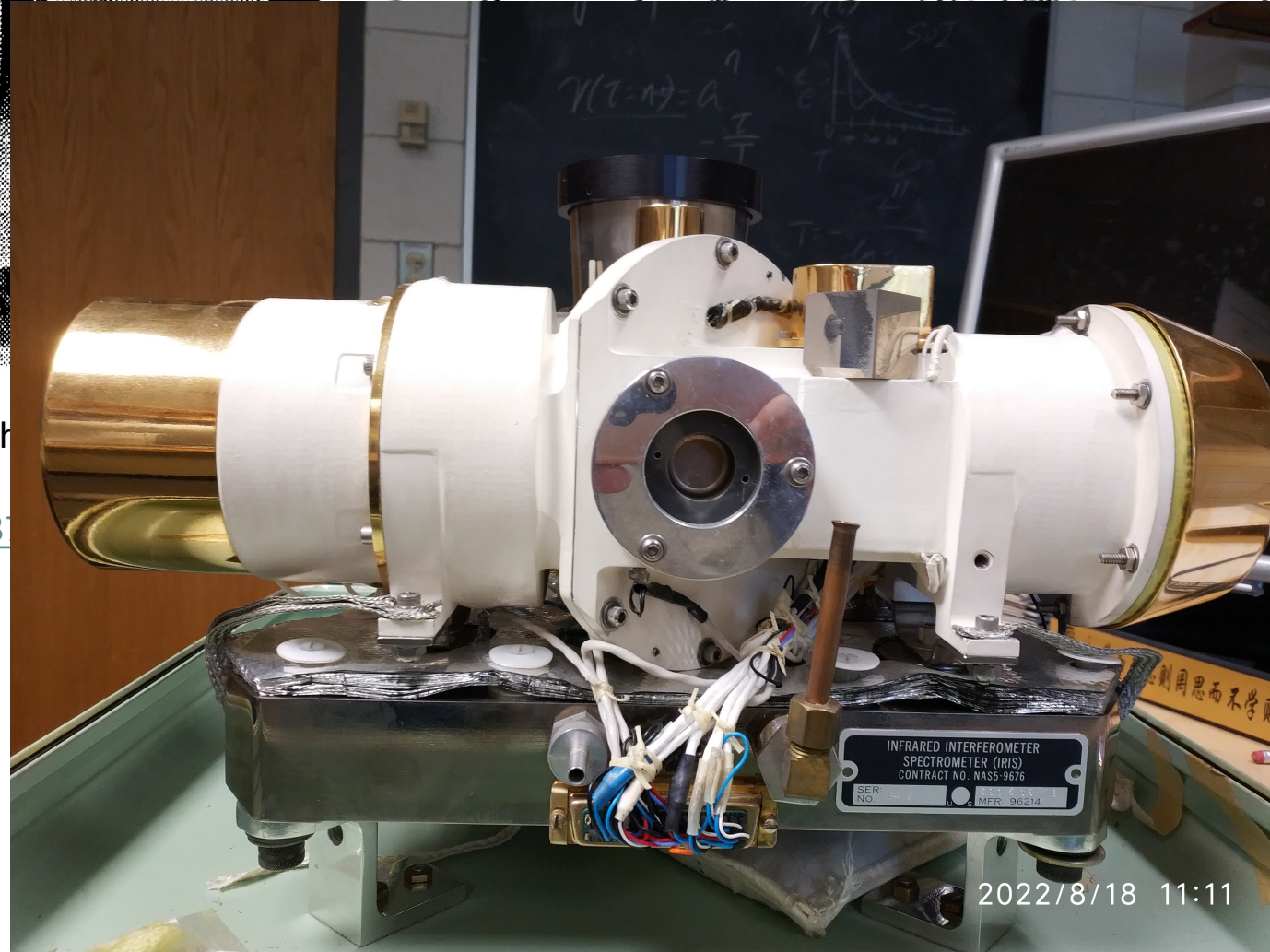
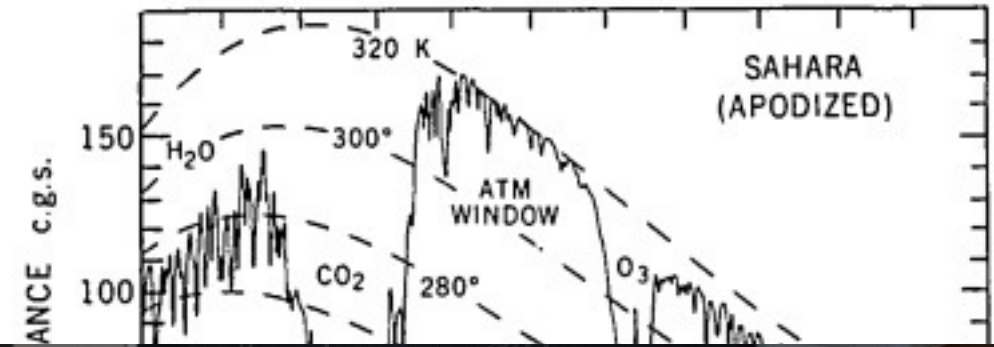


A bit more than half a century ago



R. A. Hanel, B. Schlachman, D. Rogers, D. Vanous, "Nimbus 4 Michelson Interferometer," Appl. Opt. **10**, 1376-1382 (1971);
<https://www.osapublishing.org/ao/abstract.cfm?uri=ao-10-6-1376>

IRIS-D on Nimbus IV: April 1970-January 1971



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Application of a statistical method for testing a general circulation model with spectrally resolved satellite data

Michael R. D. Haskins, Richard M. Goody, and Luke Chen
Atmospheric and Space Sciences Division, Jet Propulsion Laboratory, California Institute of Technology, Pasadena

Abstract. The motivation for this paper is to understand better the processes internal to the atmosphere. These processes, which have less than a year, define the atmosphere's response to external statistics are particularly important for testing model variability. The results of forcing the atmosphere, for example, by ocean surface increase of greenhouse gases, etc. Comparisons are presented from the infrared interferometer spectrometer (IRIS), an orbital spectrometer, and spectra calculated using the medium-resolution MODTRAN, applied to the temperature and humidity profile model. Ten months of IRIS data are available, and we have characterized deviations, skew, and kurtosis of its spectrally resolved brightness tropical regions for individual months and for a range of time comparisons of covariances using Empirical Orthogonal Functions frequency space. All data that are presented are based on radiance like spectra, which eliminates many of the errors generated by most of the errors due to calibration uncertainties in IRIS. In residuals) between the IRIS and the GCM statistics are found in that the spectral data can provide a severe test of many aspects of a general circulation model. We discuss some of the residuals and how they improve model performance in the context of an adjoint form. The only way to have confidence in the performance of a model is to have discriminating comparisons with data as are practicable, and we have relevant

MAY 1999

NOTES AND CORRESPONDENCE

Calibration of Radiances from Space

RICHARD GOODY

Falmouth, Massachusetts

ROBERT HASKINS

Jet Propulsion Laboratory, California Institute of Technology, Pasadena, California

6 March 1997 and 19 June 1997

ABSTRACT

HASKINS ET AL.

1409

Radiance Covariance and Climate Models

ROBERT HASKINS,* RICHARD GOODY, AND LUKE CHEN

Jet Propulsion Laboratory, California Institute of Technology, Pasadena, California

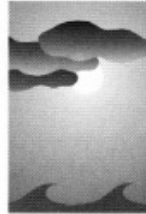
(Manuscript received 7 January 1998, in final form 1 June 1998)

ABSTRACT

Spectral empirical orthogonal functions (EOFs) derived from the covariance of satellite radiance spectra may be interpreted in terms of the vertical distribution of the covariance of temperature, water vapor, and clouds. This has been done for four major geographic regions: the tropical oceans, midlatitude oceans, and three important land areas. The purpose of the investigation is to demonstrate the important constraints that resolved spectral radiances can place upon climate models.

Detect climate change from AIRS radiances

Testing Climate Models: An Approach



Richard Goody,* James Anderson,+ and Gerald North*

ABSTRACT

The scientific merit of decadal climate projections can only be established by means of comparisons with observations. Testing of models that are used to predict climate change is of such importance that no single approach will provide the necessary basis to analyze systematic errors and to withstand critical analysis.

Appropriate observing systems must be relevant, global, precise, and calibratable against absolute standards. This paper describes two systems that satisfy these criteria: spectrometers that can measure thermal brightness temperatures with an absolute accuracy of 0.1 K and a spectral resolution of 1 cm^{-1} , and radio occultation measurements of refractivity using satellites of the GPS positioning system, which give data of similar accuracy.

Comparison between observations and model predictions requires an array of carefully posed tests. There are at least two ways in which either of these data systems can be used to provide strict, objective tests of climate models. The first looks for the emergence from the natural variability of a predicted climate “fingerprint” in data taken on different occasions. The second involves the use of high-order statistics to test those interactions that drive the climate system toward a steady state. A correct representation of these interactions is essential for a credible climate model.

A set of climate model tests is presented based upon these observational and theoretical ideas. It is an approach that emphasizes accuracy, exposes systematic errors, and is focused and of low cost. It offers a realistic hope for resolving some of the contentious arguments about global change.

- Long-term trend then optimal fingerprinting for detection and attribution
- Second-moment statistics (covariance) for model evaluation



From spectral radiance to climate

Geophysical variables

$T(z)$
$q_{H_2O}(z)$ $q_{O_3}(z)$ $q_{CH_4}(z)$...
Cloud, aerosols
$T_{skin}, \epsilon_s(\nu)$

Spectral Radiances

$$I_{TOA}(\nu; \theta, \phi)$$

Retrieve-then-average
Vs.
Average-then-retrieve

Sounding community

Detect climate change signal from
radiances (AIRS, IRIS-D, IASI, ...)

Spectral Flux

$$F_\nu = \int_0^{2\pi} d\phi \int_0^{\pi/2} I_{TOA}(\nu; \theta, \phi) \cos\theta \sin\theta d\theta$$

Spectral Radiative Feedbacks

$$\lambda_{x_\nu} = -\frac{\delta_x \bar{F}_\nu}{\delta X} \frac{\delta X}{\delta T_s}$$

Instrument cross calibration
Spectral radiative feedbacks

Broadband Radiation Budget

$$F = \int_{\Delta\nu} F_\nu d\nu$$

Broadband Radiative Feedbacks

$$\lambda_x = -\frac{\delta_x \bar{F}}{\delta X} \frac{\delta X}{\delta T_s}$$

Energy budget and feedbacks community

Assess long-term performance

With 21.9 billions of AIRS well-calibrated spectra collected so far

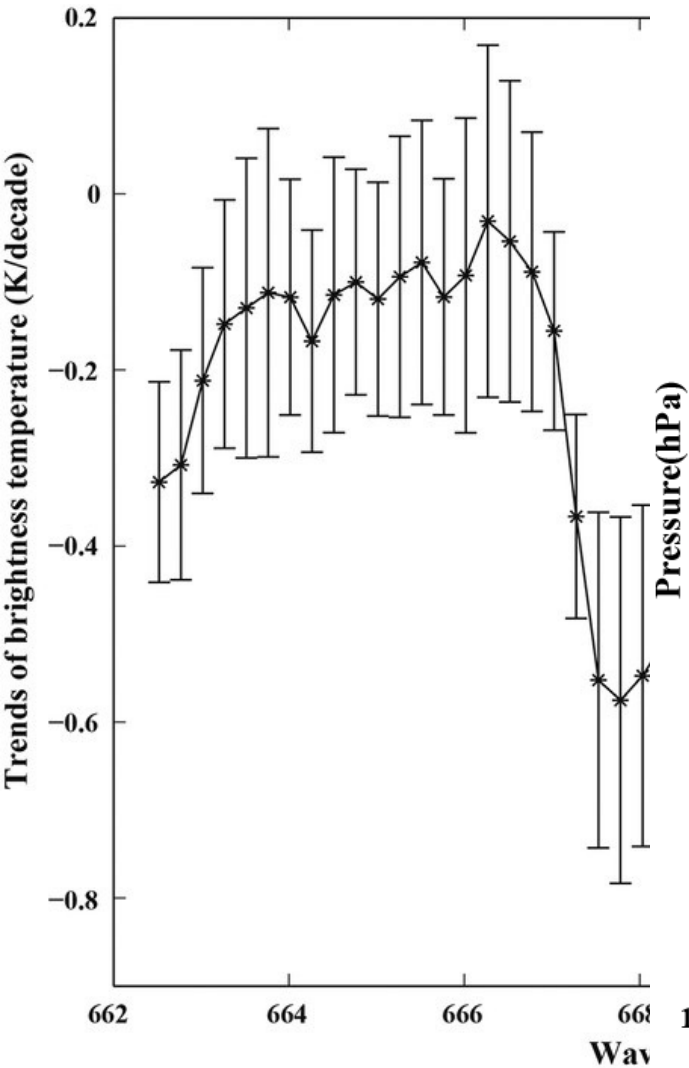
- More can be done with the spectral radiances (trend analysis, signal detection and attribution, etc.), yet complexity with angles and clouds.
- Spectral flux can be derived and used as a bridge to help us understand radiative forcings and feedbacks

Spectral OLR we derived directly from AIRS radiance now is part of standard AIRS L3 product (AIRSIL3MSOLR_6.1)

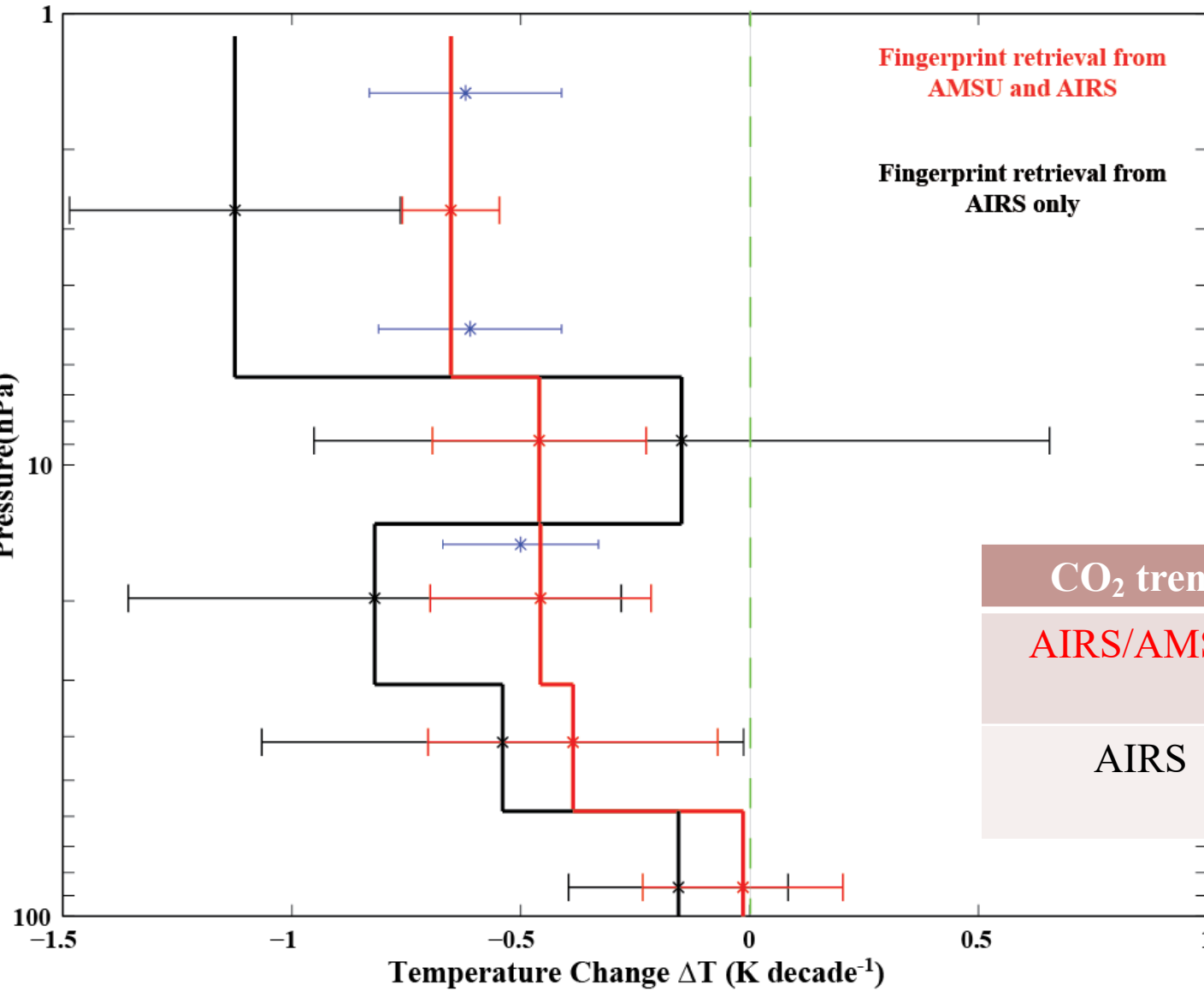
In the rest of this presentation, I will discuss a few studies and efforts in my group for the above two tasks.

AIRS nadir-view radiance trends and inferred stratospheric change (Pan et al., 2017)

Trend of 2003-2013

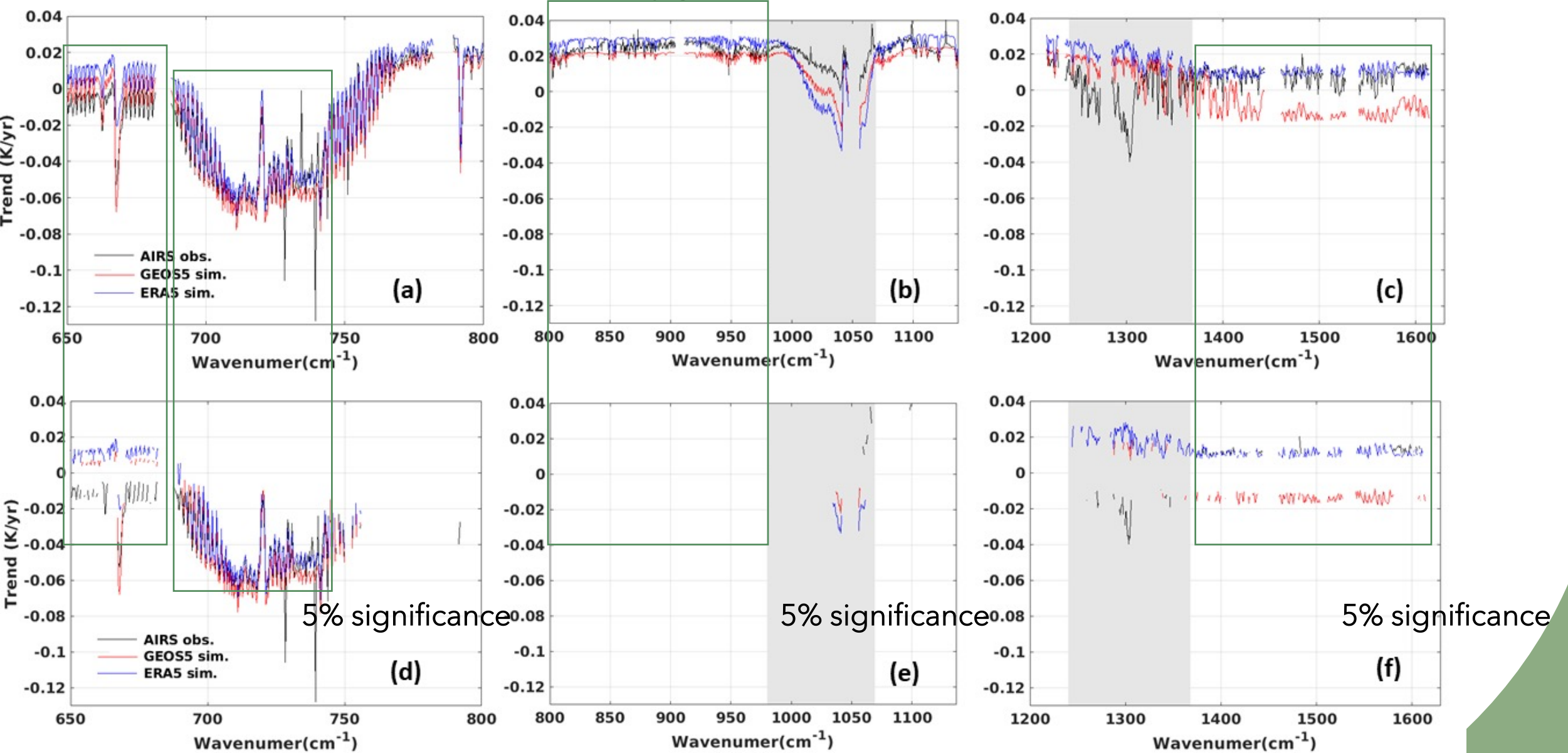


Optimal fingerprint estimation (Hasselmann, 1993;1997)



CO ₂ trend	ppmv yr ⁻¹
AIRS/AMSU	1.57 ± 0.1
AIRS	1.05 ± 0.6

AIRS nadir-view, clear-sky global-mean trend (2003-2020)



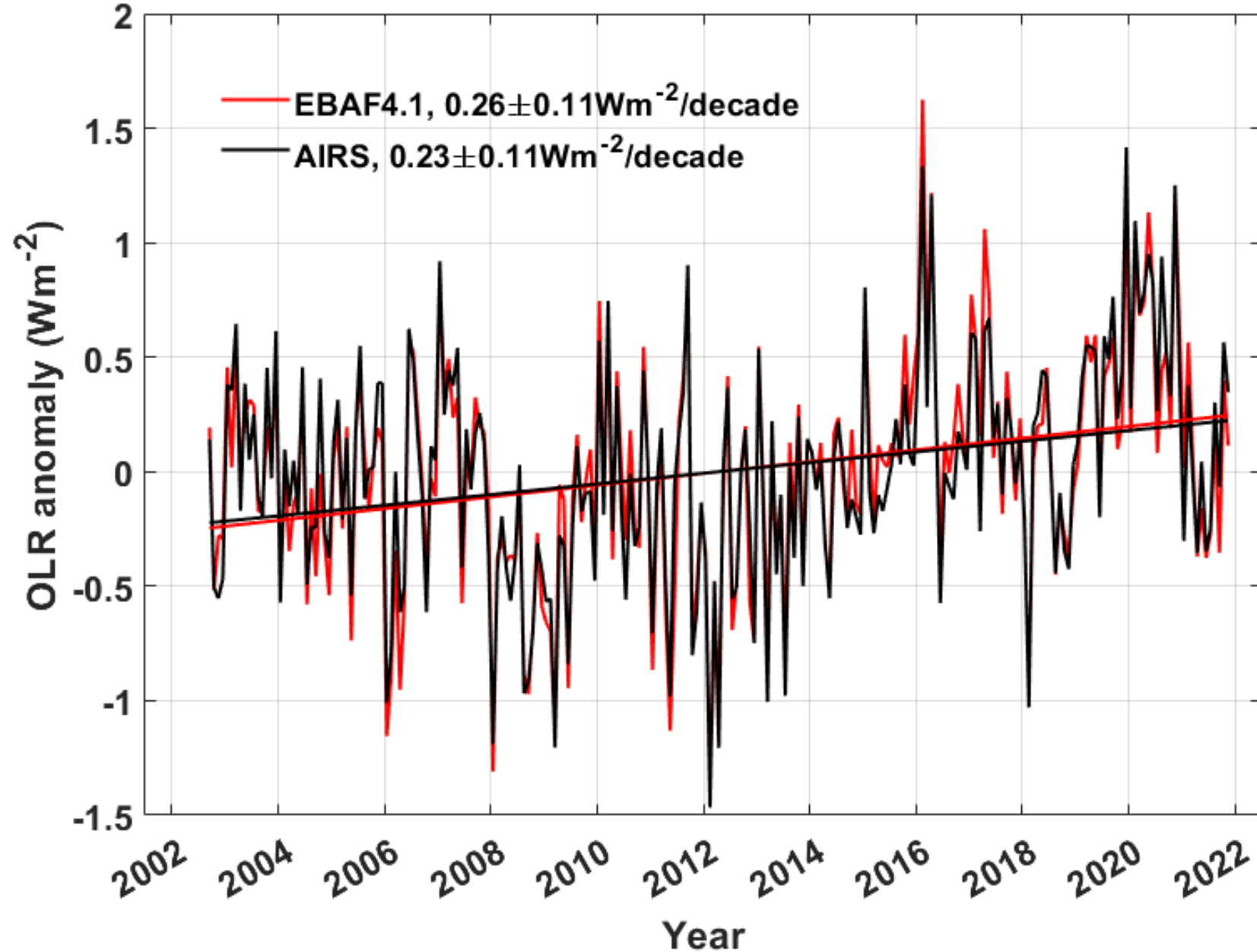
Both reanalyses sampled to AIRS clear-sky footprints before any trend analysis Huang et al. (submitted)

Next, I will use two examples to illustrate the merit of spectral flux diagnostics in feedback studies

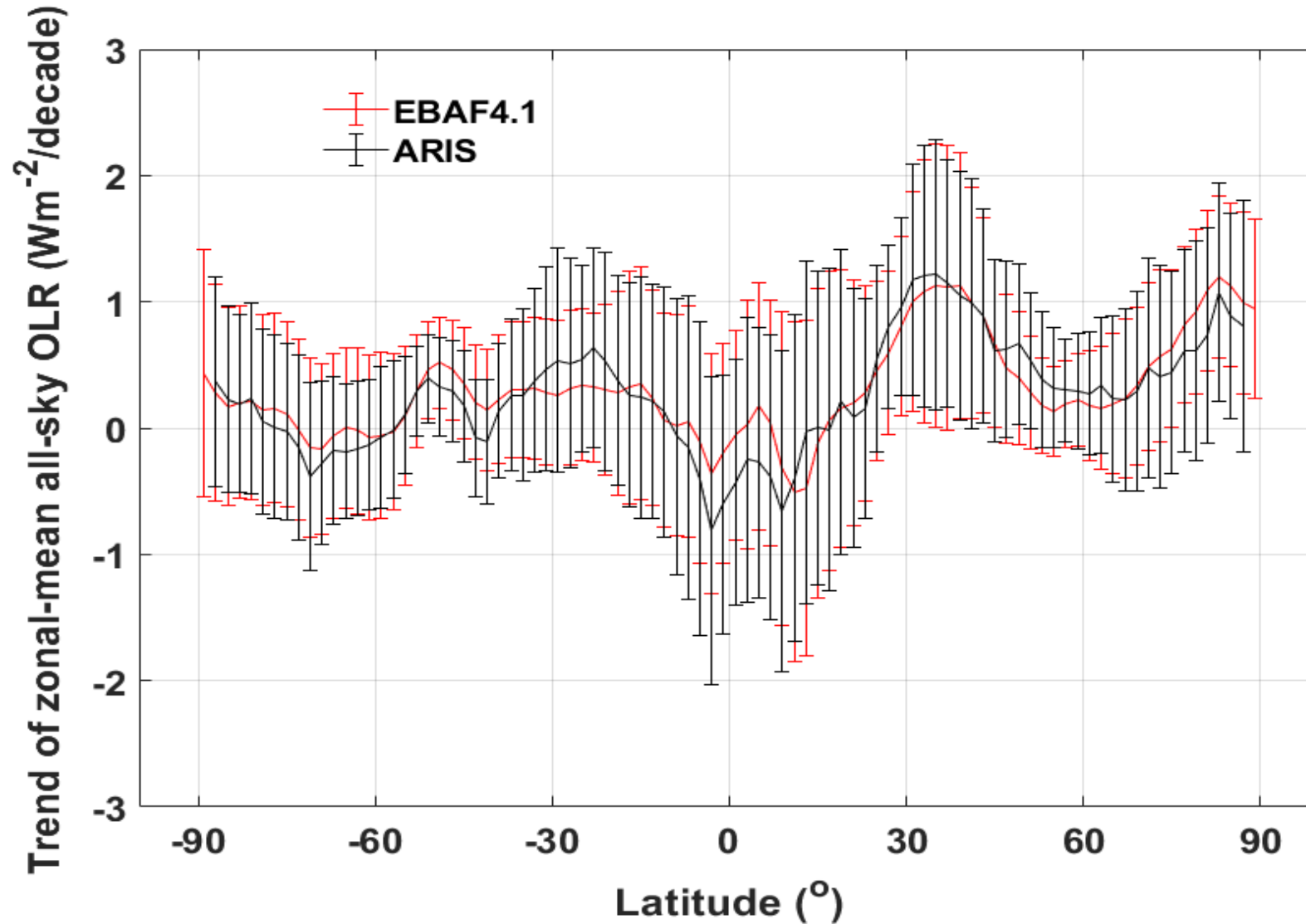
- Trends of AIRS spectra OLR vs. CERES EBAF 4.1 OLR
- Spectrally decomposed lapse-rate and relative humidity feedbacks (LW)

Spectral dimension can reveal the compensating biases that cannot be revealed from broadband diagnostics and evaluation

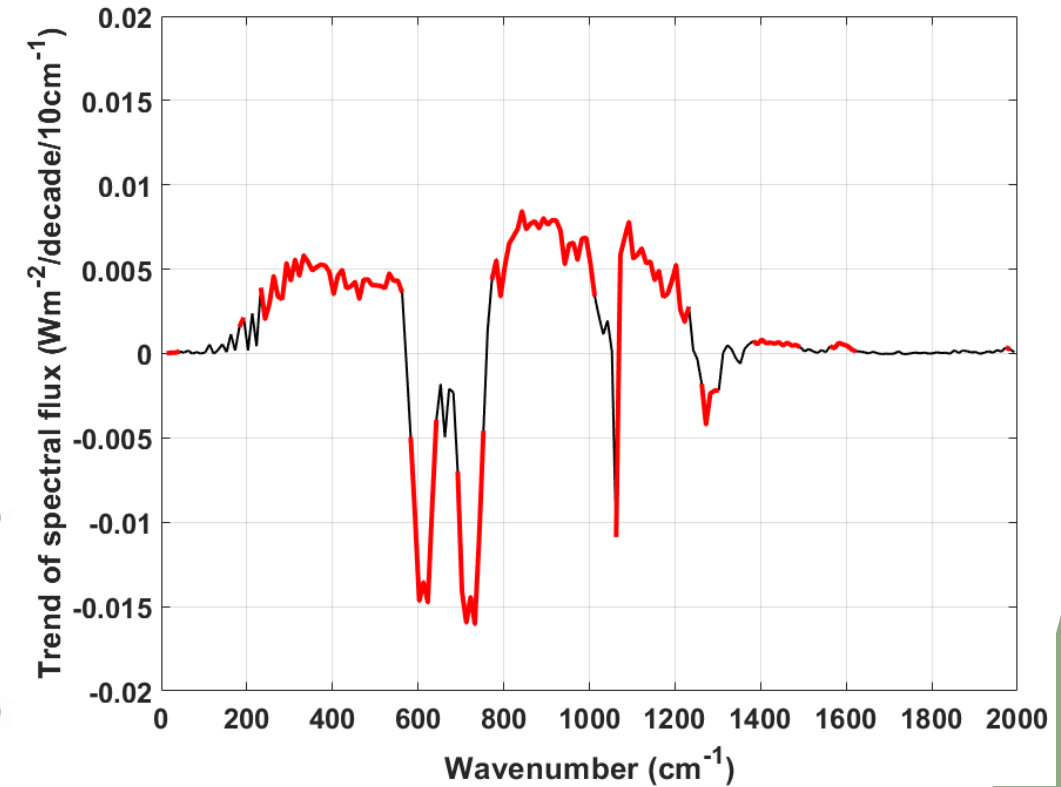
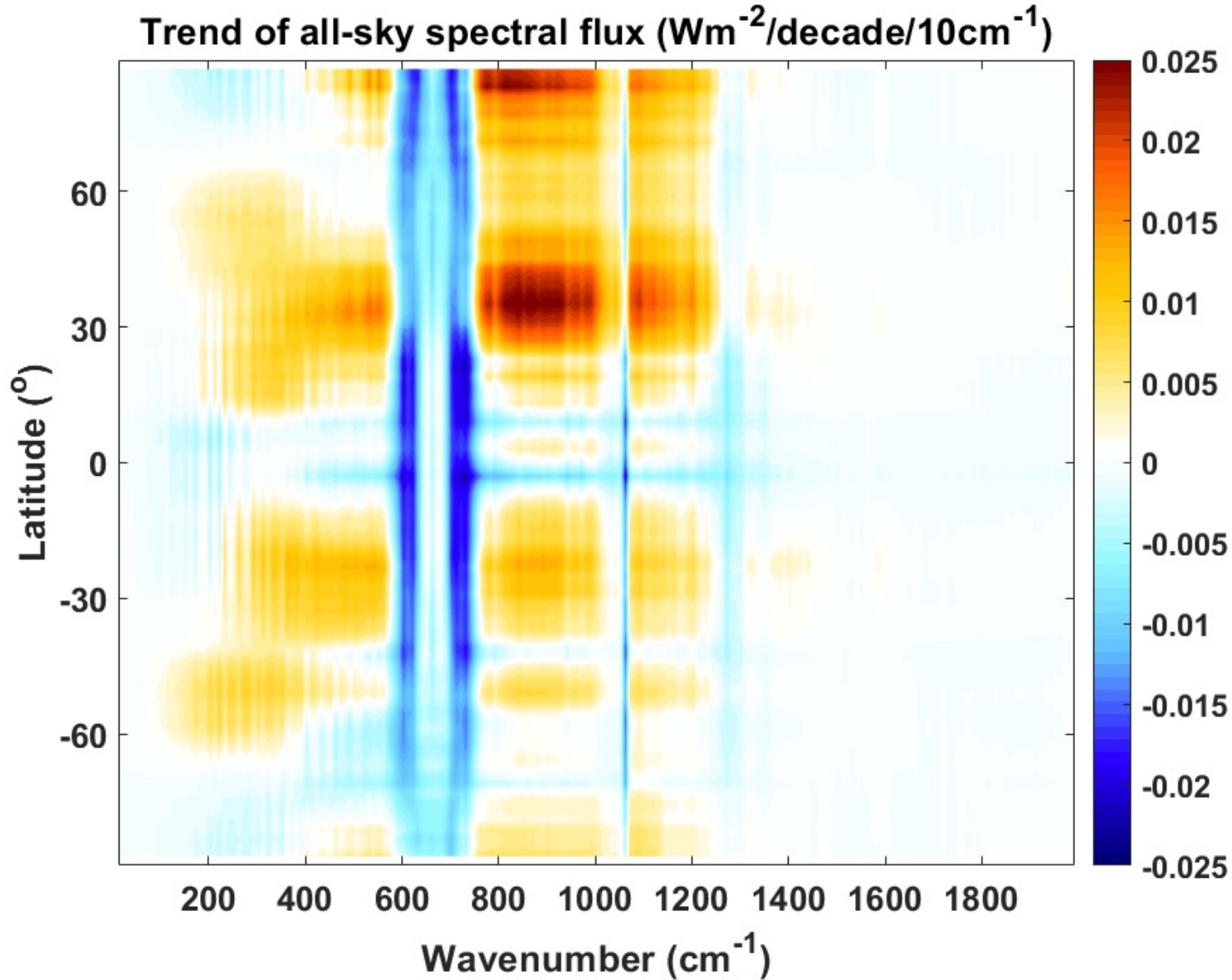
AIRS: sum of spectral OLR directly inferred from AIRS L1 radiances



Zonal-mean Trend (2003 to 2021)



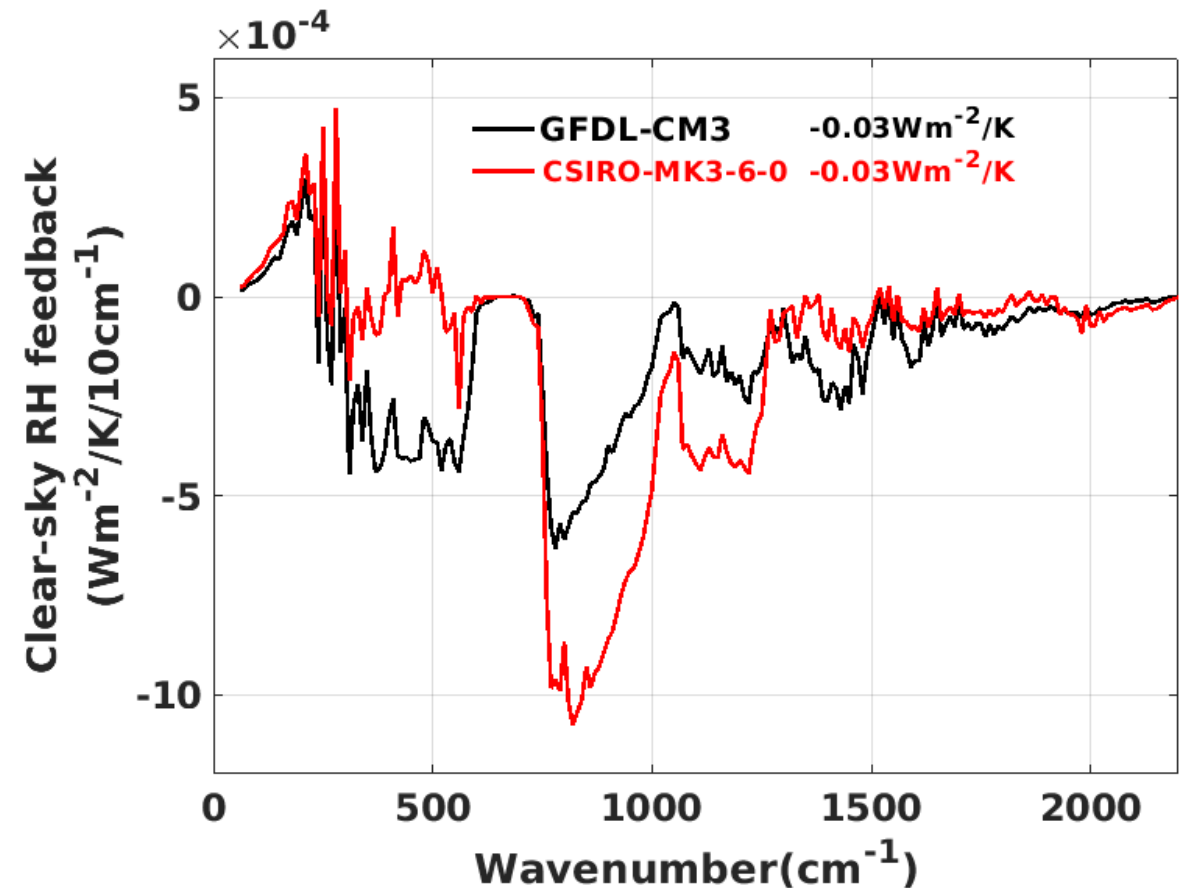
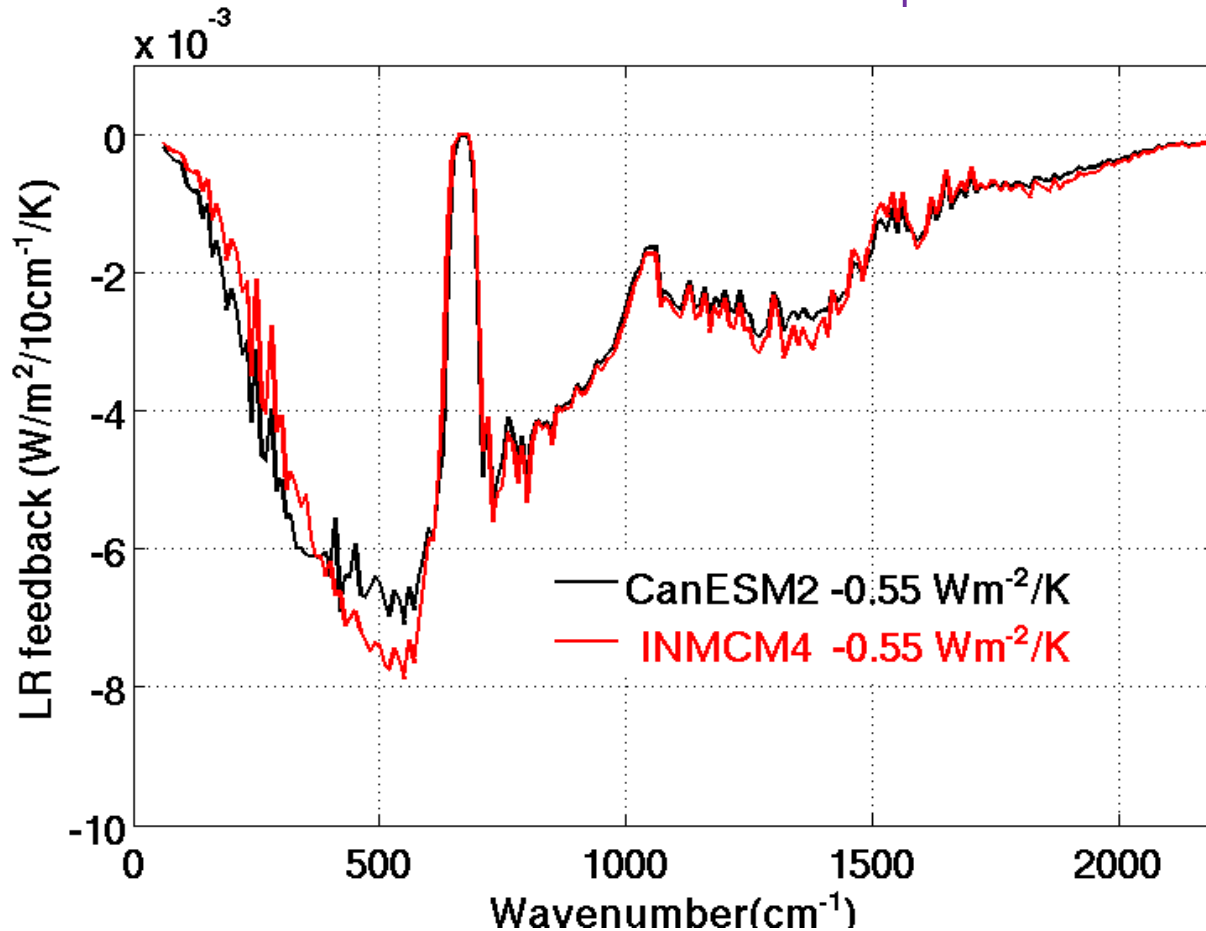
Trend of global-mean, all-sky spectral flux (2003-2021)



Spectral decomposition of the LW radiative feedbacks

Identical broadband feedback could have different spectral decomposition

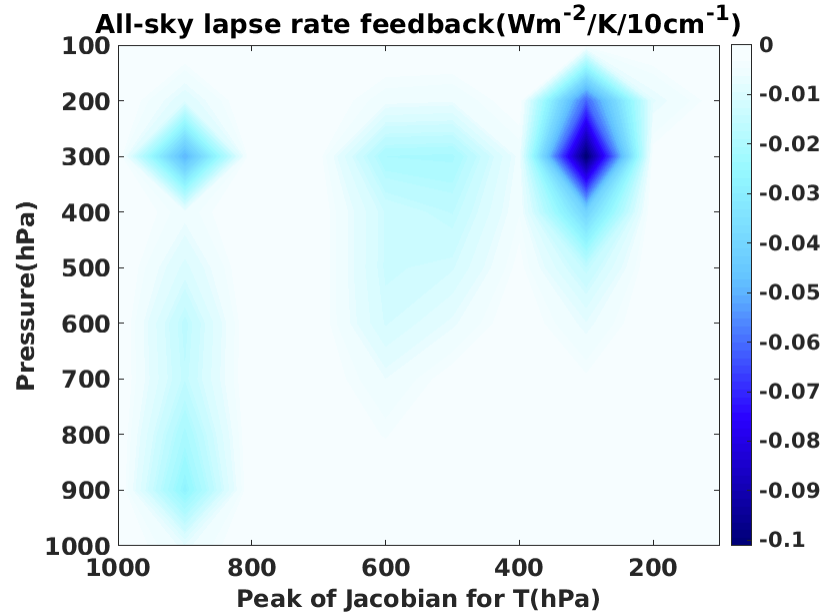
spectral interval: 10cm^{-1}



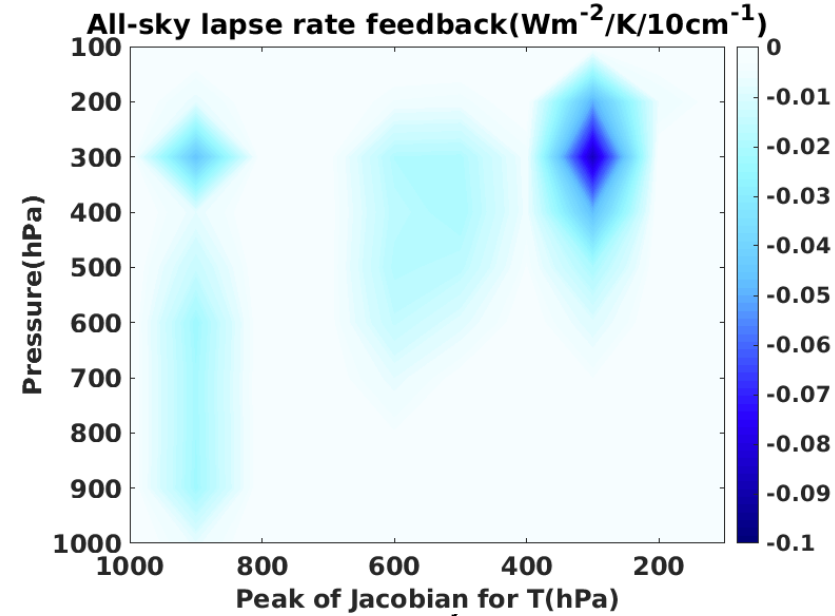
(Huang et al., 2014; Pan & Huang, 2018)

We can rearrange spectral frequency w.r.t. the peak of *clear-sky* Jacobian
&
Examine the contribution from different vertical layers

CanESM2: $-0.55 \text{ Wm}^{-2}/\text{K}$

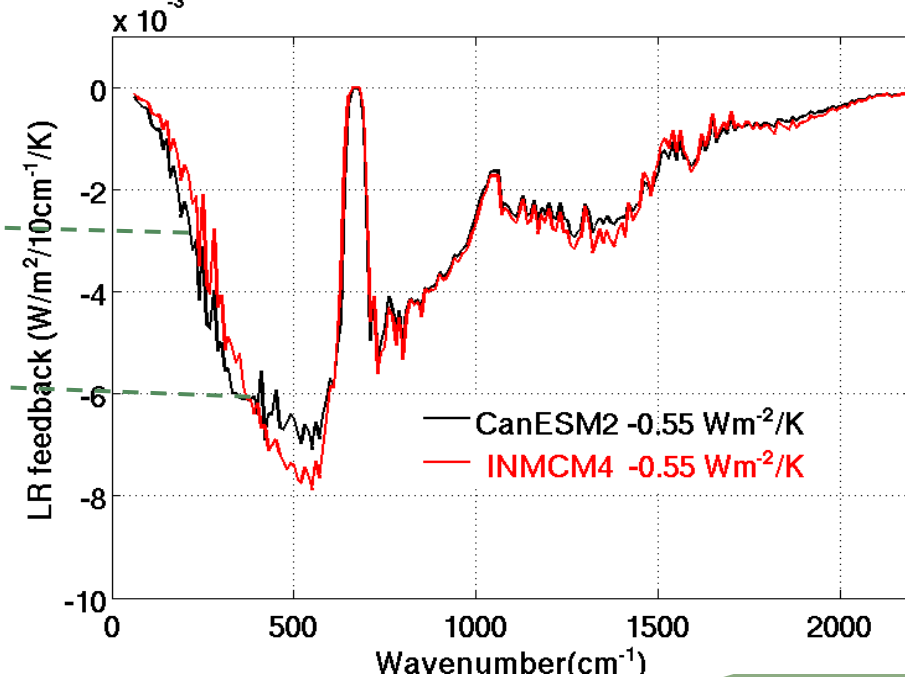
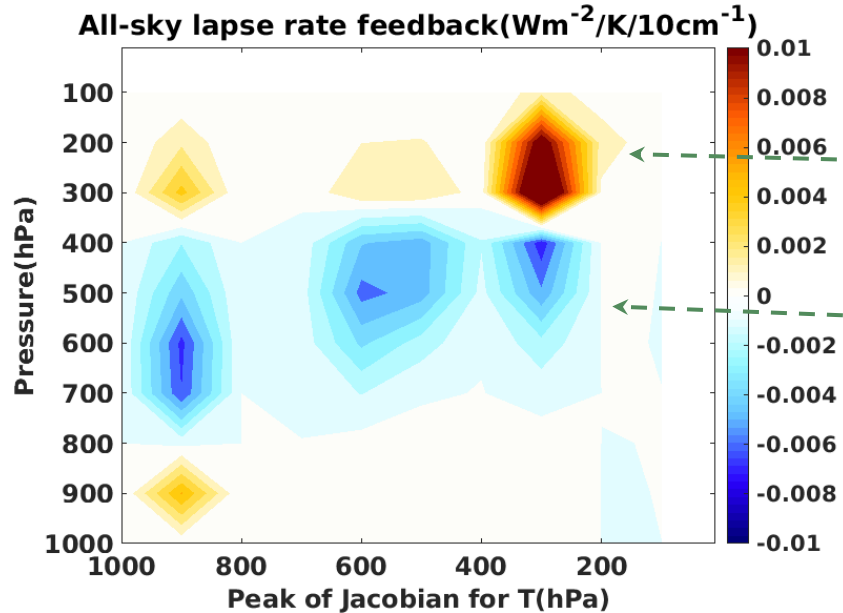


INMCM4: $-0.55 \text{ Wm}^{-2}/\text{K}$

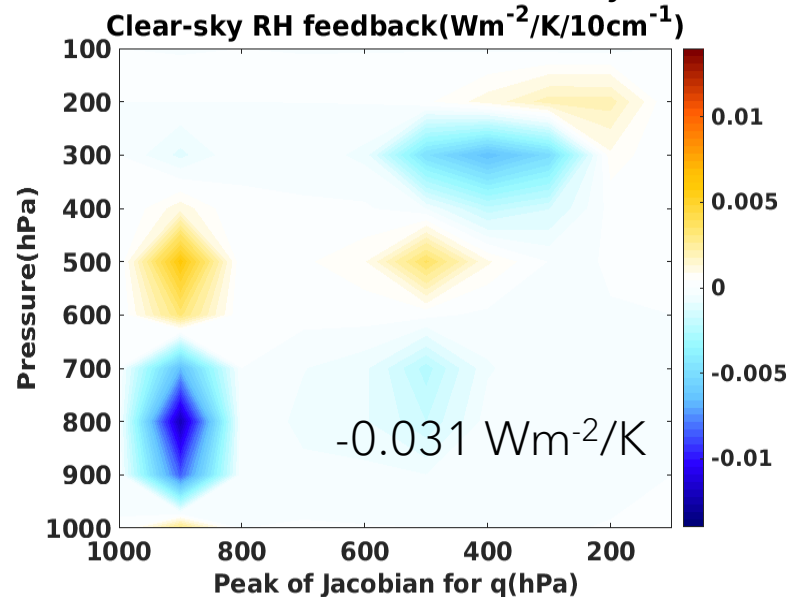


spectral interval: 10cm^{-1}

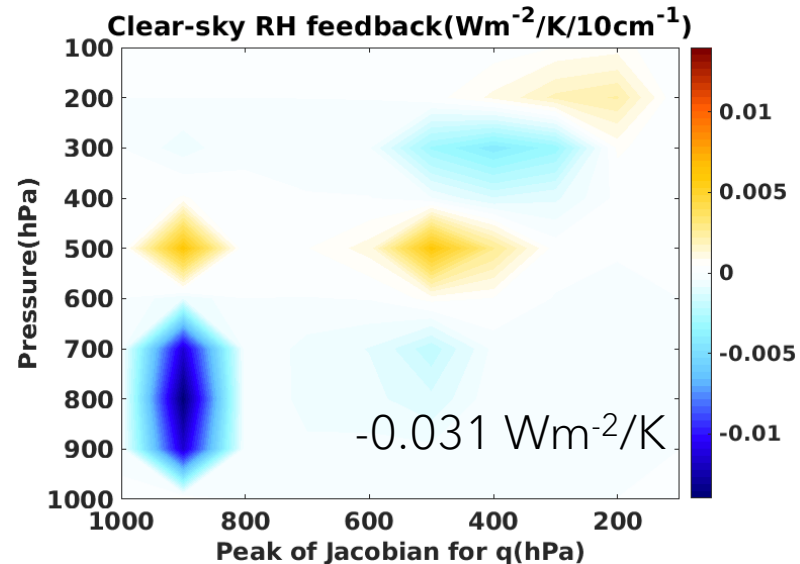
INMCM4 - CanESM2



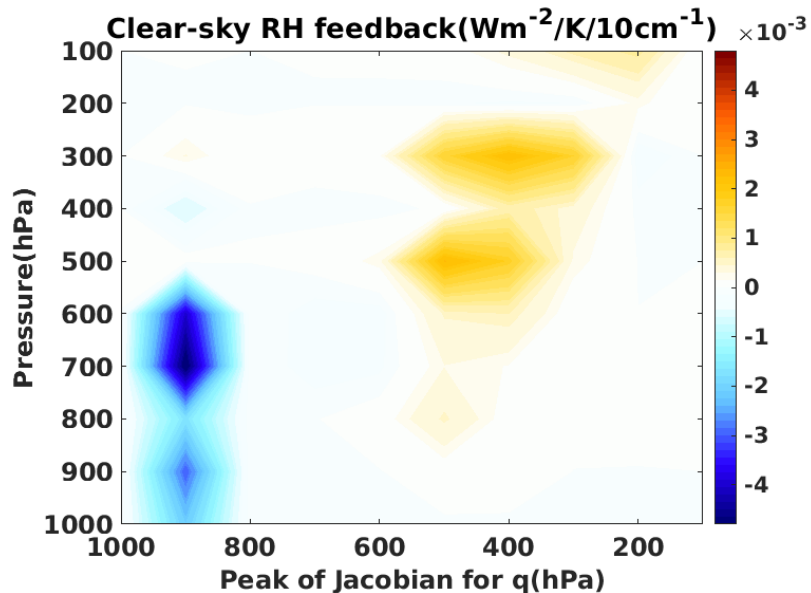
GFDL CM3 (clear-sky)



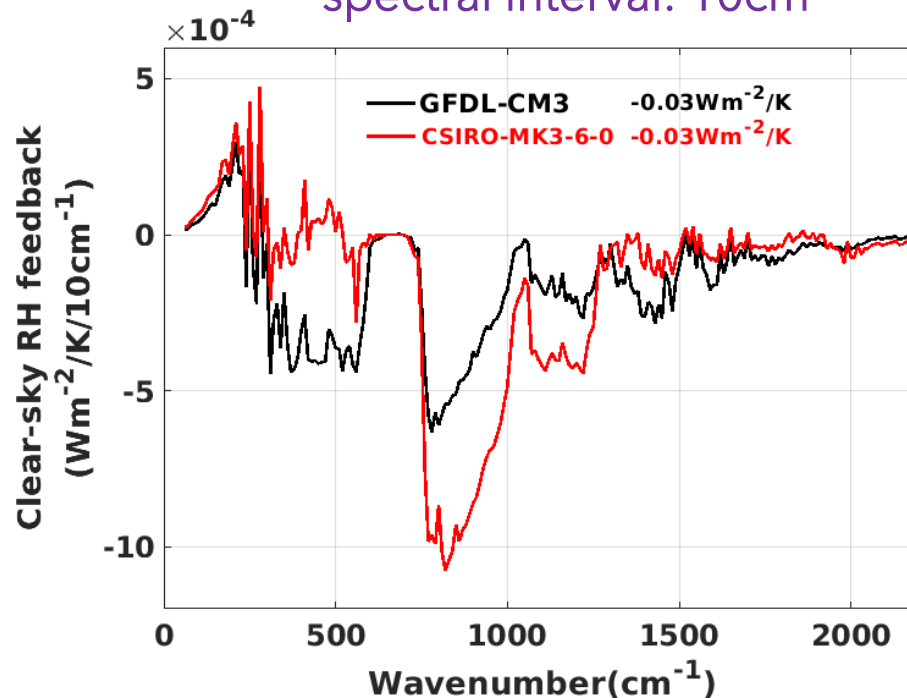
CSIRO-MK3-6-0(clear-sky)



CSIRO-MK3-6-0 - GFDL CM3



spectral interval: 10cm^{-1}



Summary and Reflections

- Complement to broadband analysis, spectral dimension can reveal the compensating biases
- However, for the longwave spectral obs: vertical information is encoded in the spectral dimension in a *complicated* way (thermal contrast, clouds, etc)
- Unscramble such vertical information is not trivial, other obs can help
- We have enough data now to seriously look at spectral radiative forcing and feedback details from the observations

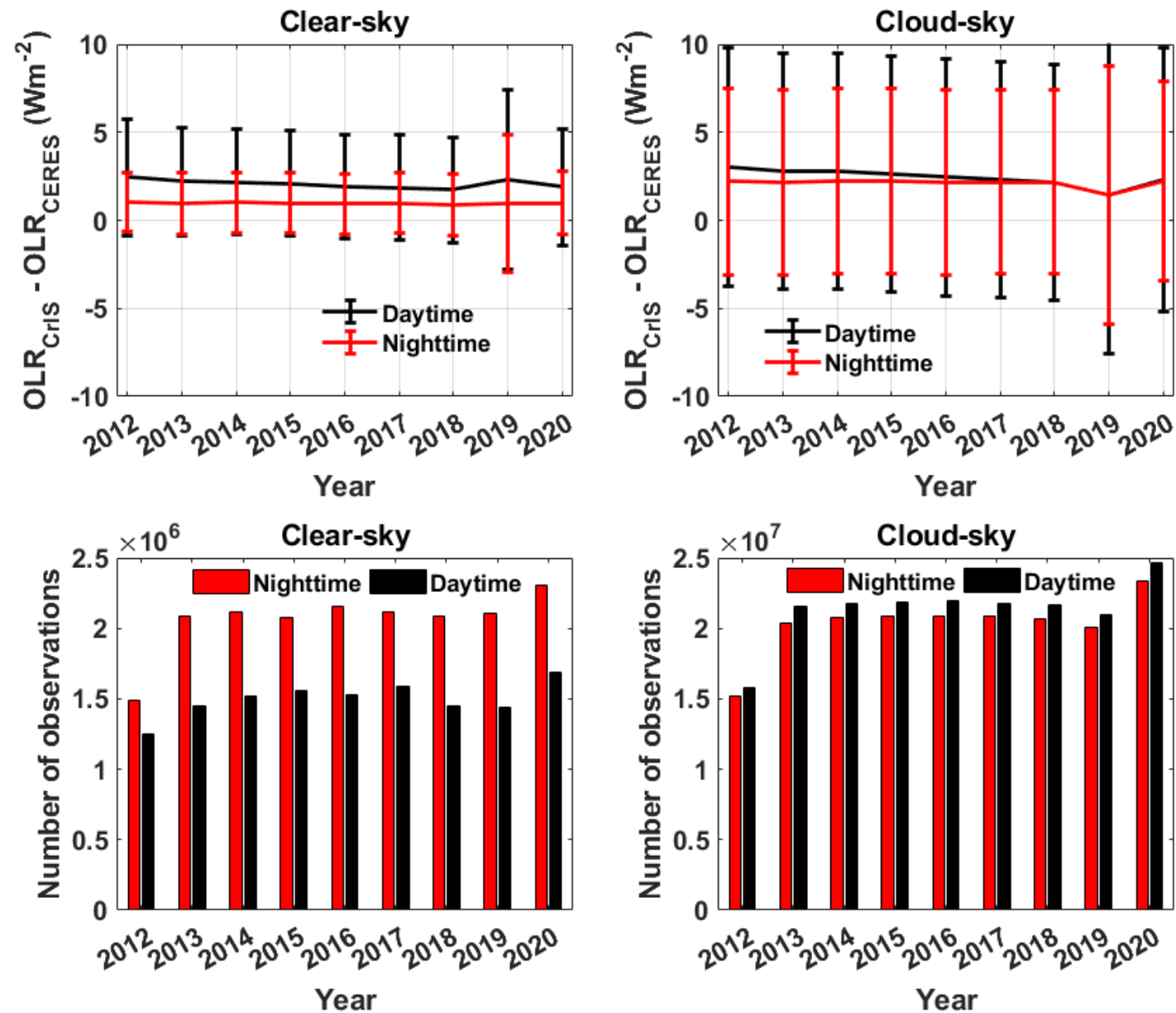
Thank You!

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Backup

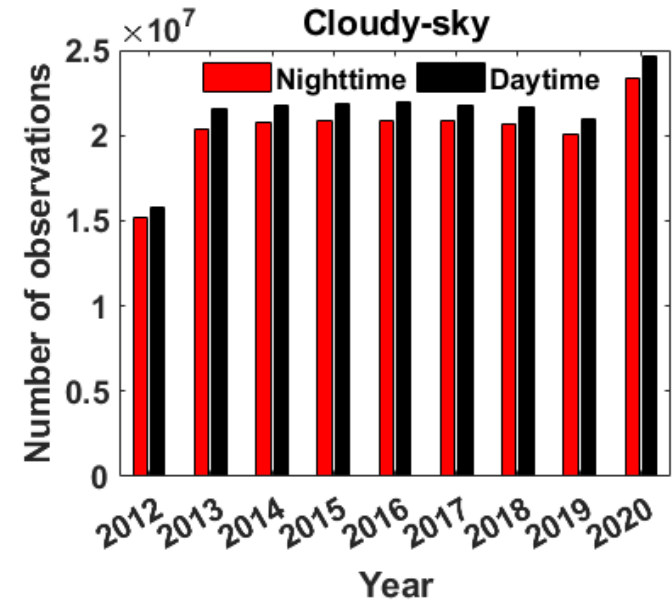
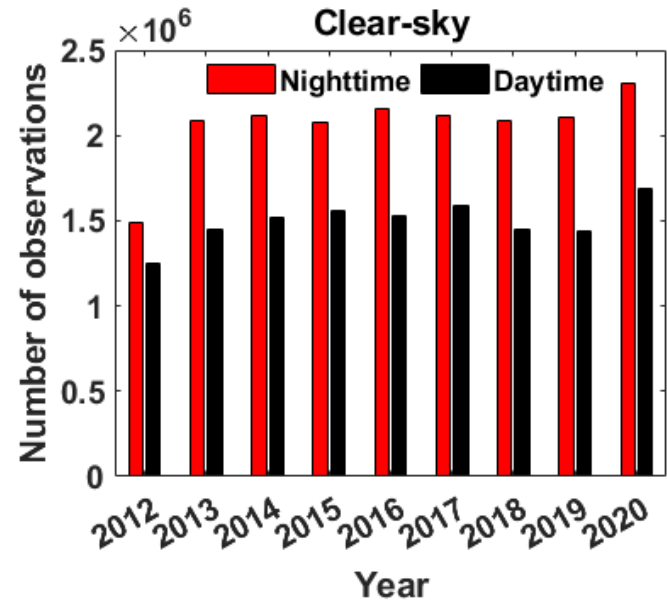
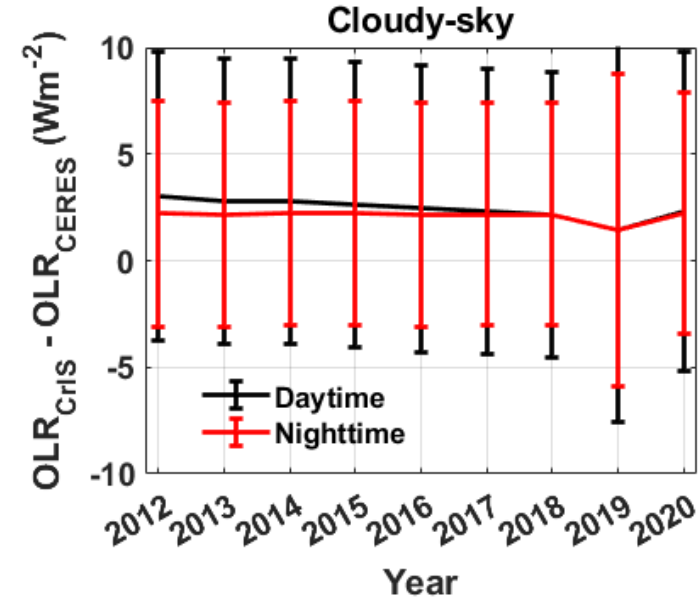
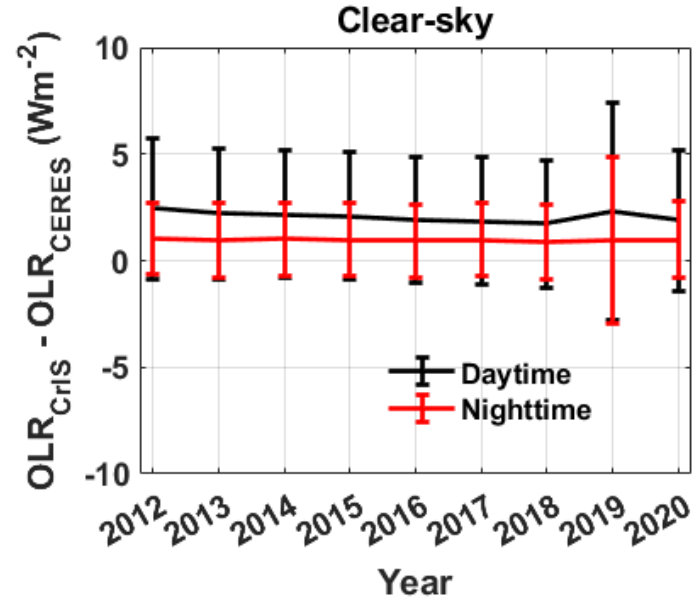
Annual means of clear-sky and cloudy-sky $OLR_{CrIS} - OLR_{CERES-FM5-Ed1}$ over the globe for 2012 to 2020



Range of the annual-mean $\text{OLR}_{\text{CrIS}} - \text{OLR}_{\text{CERES-FM5-Ed1}}$ (Wm^{-2}) from 2012 to 2020

	Clear-sky	Cloudy-sky
Daytime	[1.71, 2.43]	[1.42, 3.02]
Nighttime	[0.88, 1.03]	[1.45, 2.23]

Annual means of clear-sky and cloudy-sky $\text{OLR}_{\text{CrIS}} - \text{OLR}_{\text{CERES-FM5-Ed1}}$ over the globe for 2012 to 2020

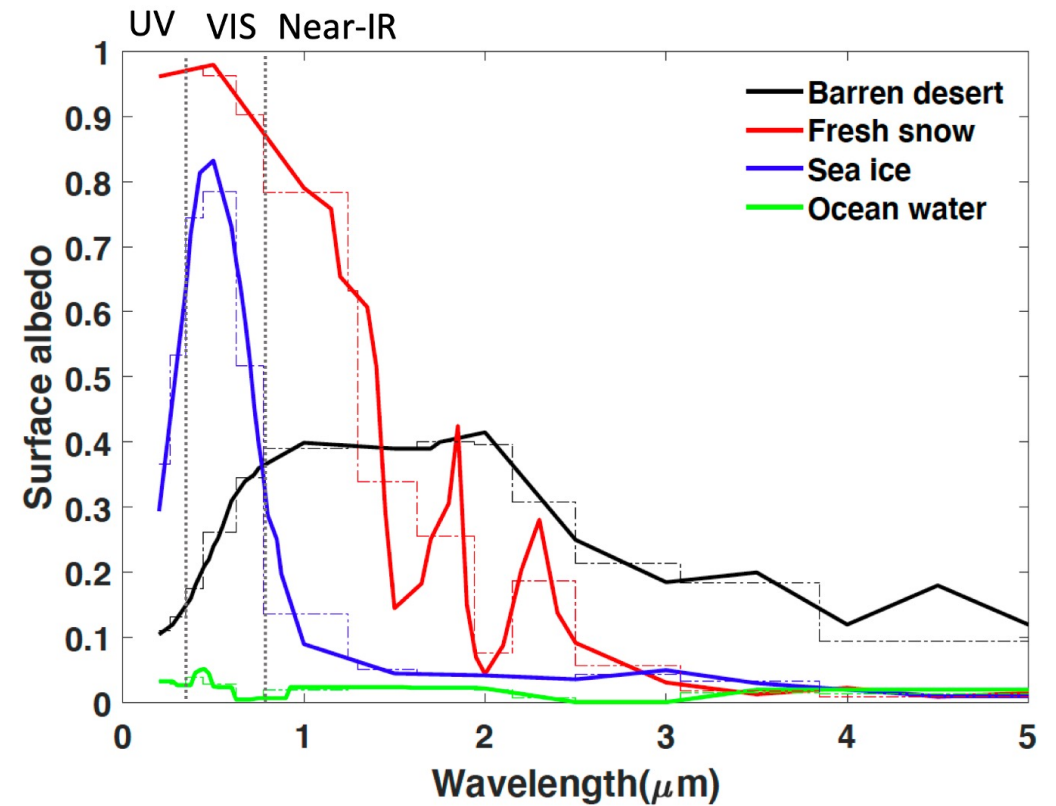
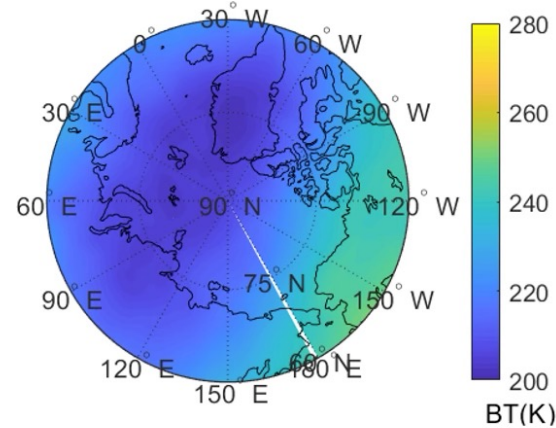
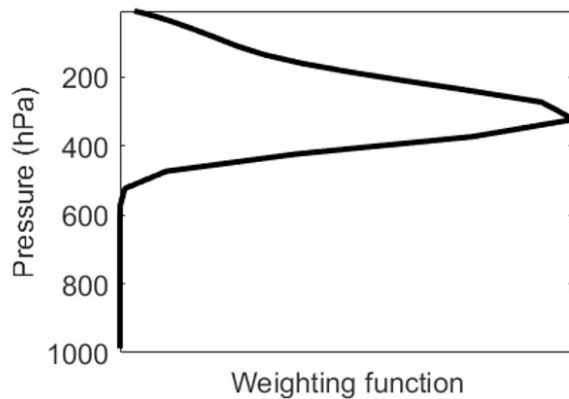
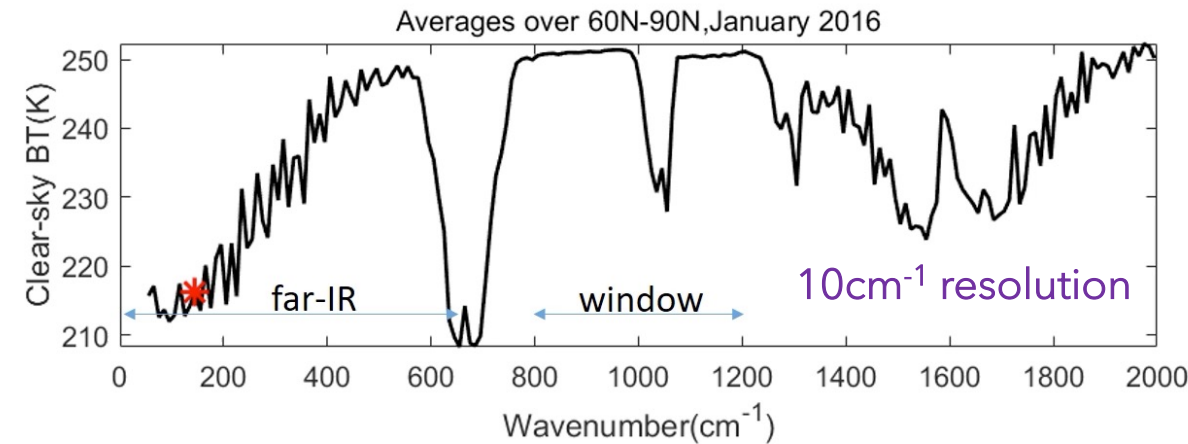


Range of the annual-mean $\text{OLR}_{\text{CrIS}} - \text{OLR}_{\text{CERES-FM5-Ed1}}$ (Wm^{-2}) from 2012 to 2020

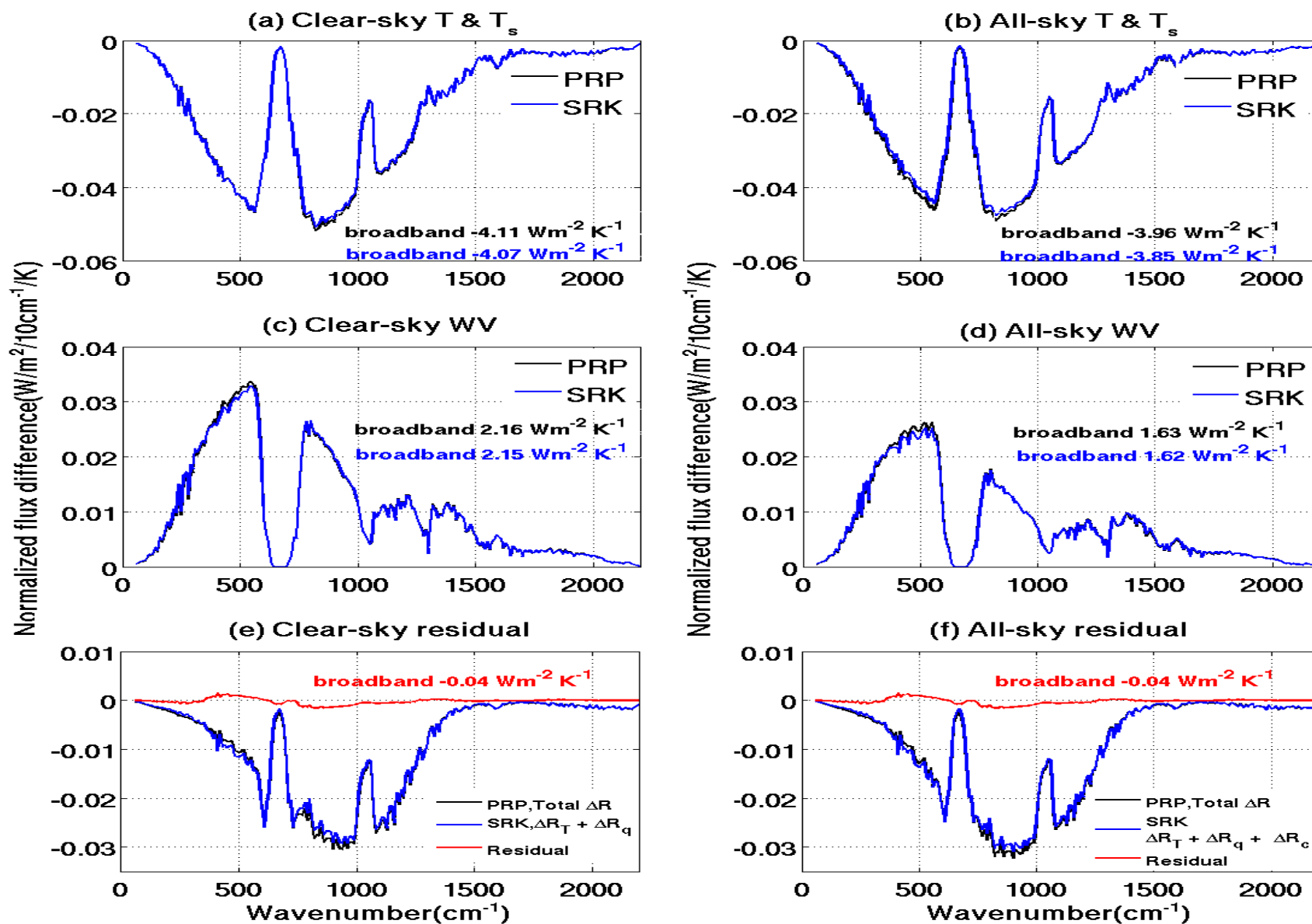
	Clear-sky	Cloudy-sky
Daytime	[1.71, 2.43]	[1.42, 3.02]
Nighttime	[0.88, 1.03]	[1.45, 2.23]

Spectral (band-by-band) flux can be more revealing than the broadband flux

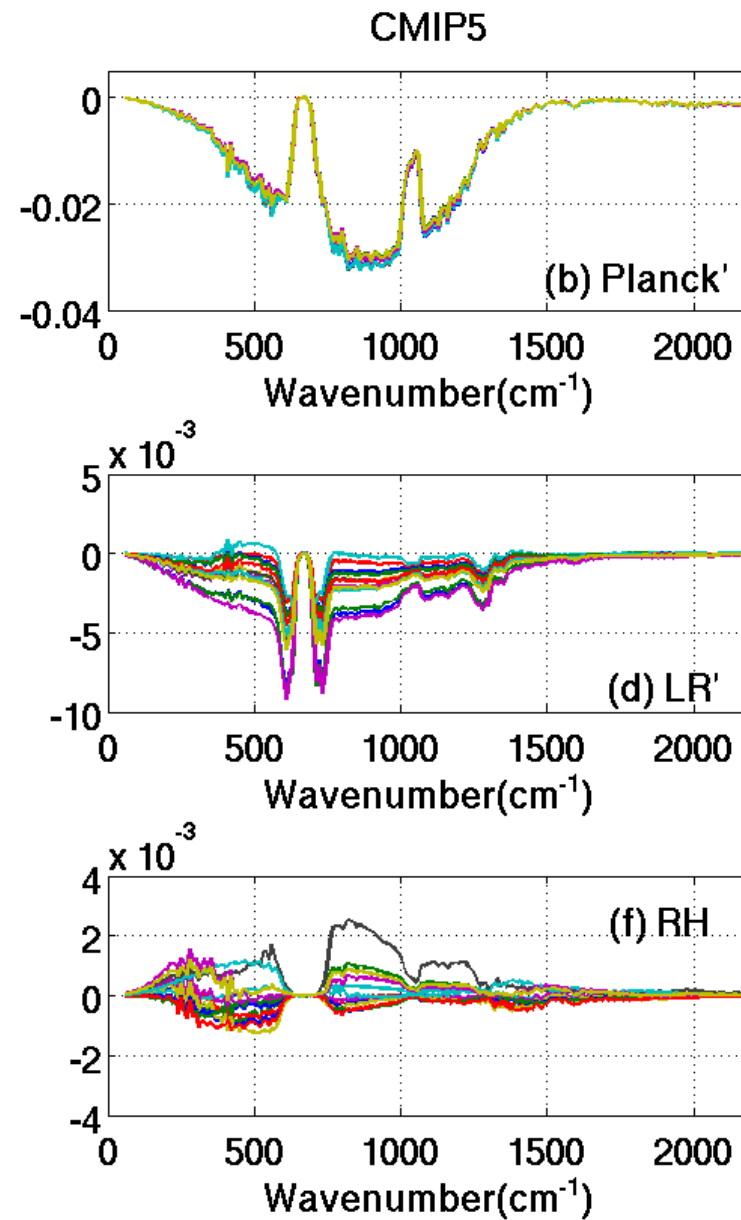
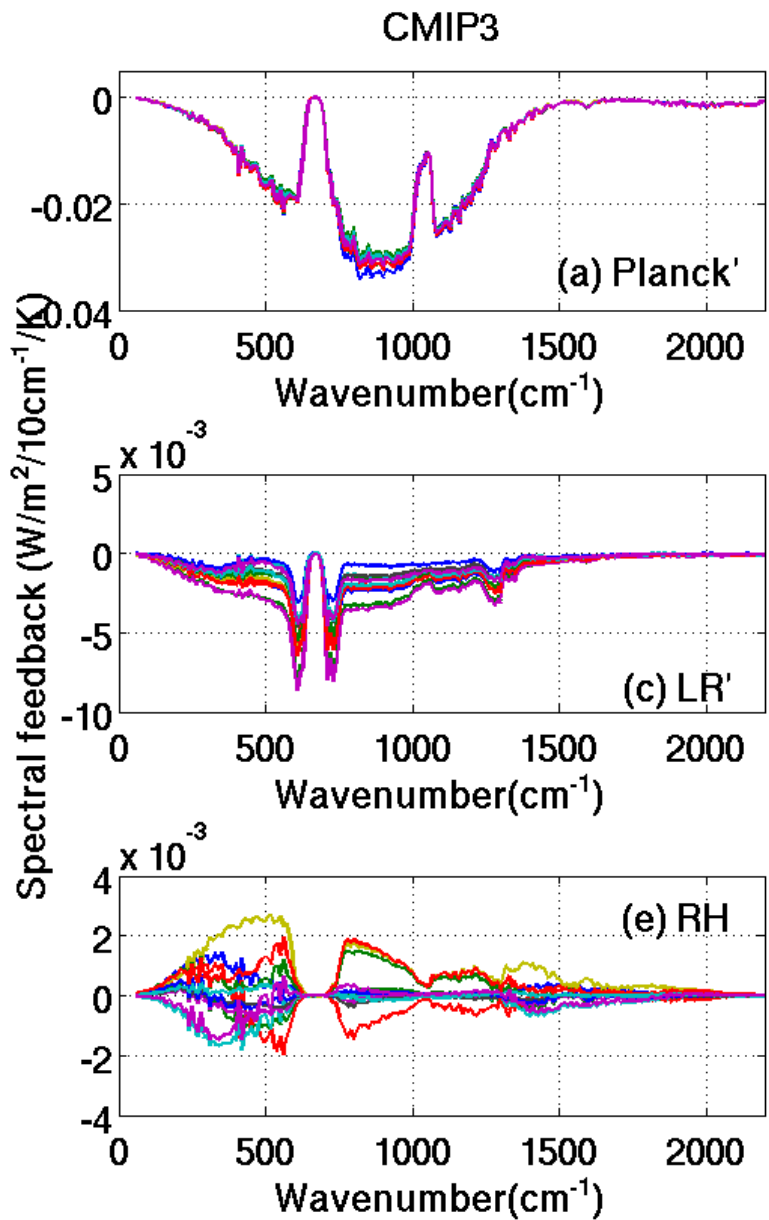
- LW spectral channel/band: sensitive to different part of the atmosphere (cloud can "mess" it up)
- SW spectral channel/band: dichotomy between visible and near-IR (surface albedo, gas absorption)



Validation: comparisons with the PRP results



(Huang et al., 2014)



spectral interval: 10cm^{-1}

(Huang et al., 2014)

(Pan and Huang, 2018)

Using RH as a state variable

